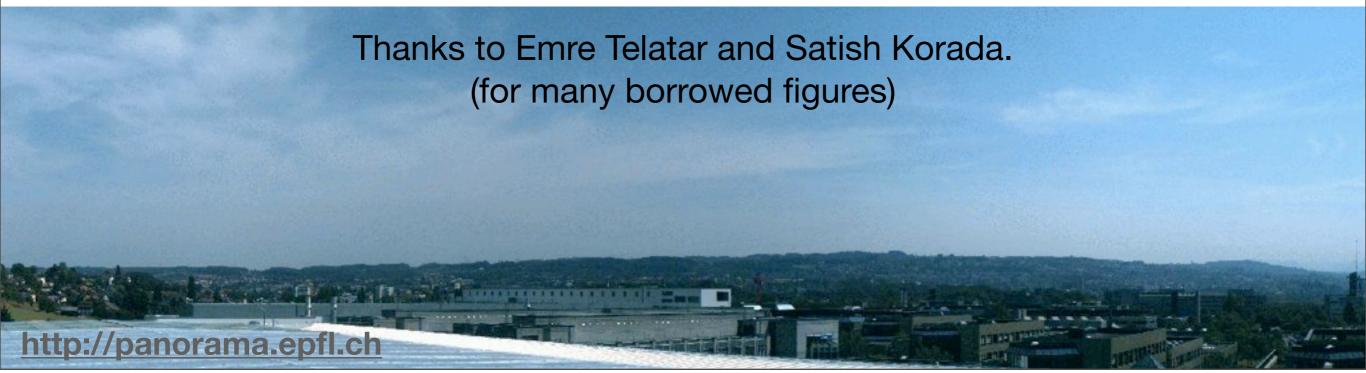


# Polar Codes -- A New Paradigm for Coding

R. Urbanke, EPFL

Physics of Algorithms, Santa Fe, September 2nd, 2009





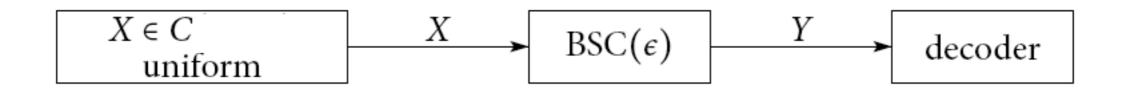




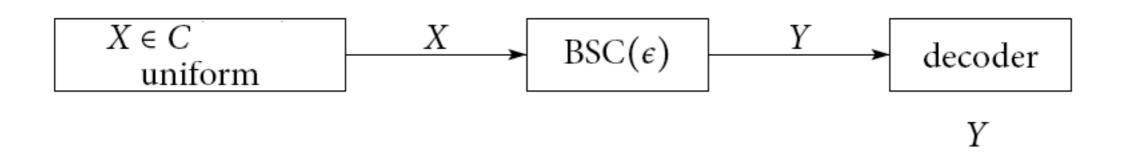


# Coding

# Coding



# Coding



# Important Parameters

## Important Parameters

 $(r, P, \chi_E, \chi_D, n)$ 

rate, error probability, encoding complexity, decoding complexity, blocklength

$$C(G) = \left\{ x \in \mathbb{F}^n : x = uG, u \in \mathbb{F}^k \right\}$$

$$G = \left(\begin{array}{cccccccc} 1 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 \end{array}\right)$$

generator matrix

$$C(G) = \left\{x \in \mathbb{F}^n : x = uG, u \in \mathbb{F}^k\right\} \qquad C = \left\{x \in \mathbb{F}^n : x = uG, u \in \mathbb{F}^k\right\} = \left\{x \in \mathbb{F}^n : Hx^T = 0^T\right\}$$

$$G = \begin{pmatrix} 1 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 \end{pmatrix} \qquad H = \begin{pmatrix} 1 & 1 & 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 & 1 \end{pmatrix}$$

generator matrix

parity-check matrix

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generator matrix

parity-check matrix

## Bitwise MAP Decoding

$$\hat{x}_{i}^{\text{MAP}}(y) = \operatorname{argmax}_{x_{i} \in \{\pm 1\}} p_{X_{i} \mid Y}(x_{i} \mid y)$$

$$(\text{law of total probability}) = \operatorname{argmax}_{x_{i} \in \{\pm 1\}} \sum_{\sim x_{i}} p_{X \mid Y}(x \mid y)$$

$$(\text{Bayes'}) = \operatorname{argmax}_{x_{i} \in \{\pm 1\}} \sum_{\sim x_{i}} p_{Y \mid X}(y \mid x) p_{X}(x)$$

$$(2.13) = \operatorname{argmax}_{x_{i} \in \{\pm 1\}} \sum_{\sim x_{i}} \left(\prod_{j} p_{Y_{j} \mid X_{j}}(y_{j} \mid x_{j})\right) \mathbb{1}_{\{x \in C\}},$$

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$$(2.13) = \operatorname{argmax}_{x_{i} \in \{\pm 1\}} \sum_{\sim x_{i}} \left(\prod_{j} p_{Y_{j} \mid X_{j}}(y_{j} \mid x_{j})\right) \mathbb{1}_{\{x \in C\}},$$

$$\operatorname{argmax}_{x_i \in \{\pm 1\}} \sum_{n \in \mathbb{N}} \left( \prod_{i=1}^{7} p_{Y_i \mid X_j} (y_j \mid x_j) \right) \mathbb{1}_{\{x_1 + x_2 + x_4 = 0\}} \mathbb{1}_{\{x_3 + x_4 + x_6 = 0\}} \mathbb{1}_{\{x_4 + x_5 + x_7 = 0\}}$$

$$H = \begin{pmatrix} x_1 & x_2 & x_3 & x_4 & x_5 & x_6 & x_7 \\ 1 & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 1 \end{pmatrix}$$

$$p(y_1 \ x_7)$$

$$p(y_6 \ x_6)$$

$$p(y_5 \ x_5)$$

$$p(y_4 \ x_4)$$

$$p(y_2 \ x_2)$$

$$p(y_1 \ x_1)$$

$$p(y_1 \ x_1)$$

[LDPC -- Gallager '60]

Erdal Arikan, ISIT 2007

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information theoretic view why codes work

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many possible variations on the theme

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many possible variations on the theme

codes not only good for channel coding; work equally well for source coding and more complicated scenarios

## References

### References

#### arXiv:0807.3917 [ps, pdf, other]

#### Channel polarization: A method for constructing capacity-achieving codes for symmetric binaryinput memoryless channels

Erdal Arikan

Comments: 49 pages, 14 figures. Submitted to IEEE Transactions on Information Theory, Oct. 2007

Subjects: Information Theory (cs.IT)

#### arXiv:0807.3806 [ps, pdf, other]

#### On the Rate of Channel Polarization

Erdal Arikan, Emre Telatar

Comments: 10 pages

Subjects: Information Theory (cs.IT)

#### arXiv:0901.2370 [ps, pdf, other]

#### Polar Codes for Channel and Source Coding

Nadine Hussami, Satish Babu Korada, Rudiger Urbanke

Comments: submitted to ISIT

Subjects: Information Theory (cs.IT)

#### arXiv:0901.0536 [ps, pdf, other]

#### Polar Codes: Characterization of Exponent, Bounds, and Constructions

Satish Babu Korada, Eren Sasoglu, Rudiger Urbanke

Comments: Submitted to IEEE Transactions on Information Theory, minor updates

Subjects: Information Theory (cs.IT)

#### arXiv:0901.2207 [ps, pdf, other]

#### Performance and Construction of Polar Codes on Symmetric Binary-Input Memoryless Channels

Ryuhei Mori, Toshiyuki Tanaka

Comments: 5 pages, 3 figures, submitted to ISIT2009

Subjects: Information Theory (cs.IT)

#### arXiv:0903.0307 [ps, pdf, other]

#### Polar Codes are Optimal for Lossy Source Coding

Satish Babu Korada, Rudiger Urbanke

Comments: 15 pages, submitted to Transactions on Information Theory

Subjects: Information Theory (cs.IT)

#### arXiv:0907.3291 [ps, pdf, other]

#### The Compound Capacity of Polar Codes

S. Hamed Hassani, Satish Babu Korada, Ruediger Urbanke

Comments: 5 pages

Subjects: Information Theory (cs.IT)

#### arXiv:0908.0302 [ps, pdf, other]

#### Polarization for arbitrary discrete memoryless channels

Eren Sasoglu, Emre Telatar, Erdal Arikan

Comments: 12 pages

Subjects: Information Theory (cs.IT)

$$G_2 = \left[ egin{array}{ccc} 1 & 0 \\ 1 & 1 \end{array} 
ight]$$

$$G_2^{\otimes 2} = \left[ egin{array}{cc} G_2 & 0 \ G_2 & G_2 \end{array} 
ight]$$

$$G_2^{\otimes 2} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix}$$

$$G_2^{\otimes 3} = \left[ egin{array}{cccc} G_2 & 0 & 0 & 0 \ G_2 & G_2 & 0 & 0 \ G_2 & 0 & G_2 & 0 \ G_2 & G_2 & G_2 & G_2 \end{array} 
ight]$$

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length  $N = 2^m$ ,  $m \in \mathbb{N}$ 

$$G_2^{\otimes 3} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

length  $N = 2^m$ ,  $m \in \mathbb{N}$ 

generator matrix: rows of  $G_2^{\otimes m}$ 

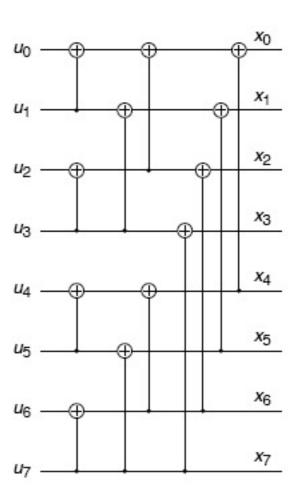
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$$\bar{x} = [u_0 \ u_1 \ u_2 \ u_3 \ u_4 \ u_5 \ u_6 \ u_7] G_2^{\otimes 3}$$

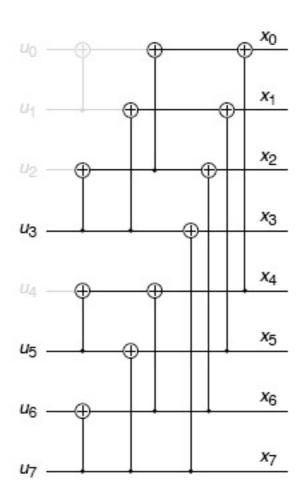


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$$\bar{x} = [0\ 0\ 0\ u_3\ 0\ u_5\ u_6\ u_7]G_2^{\otimes 3}$$

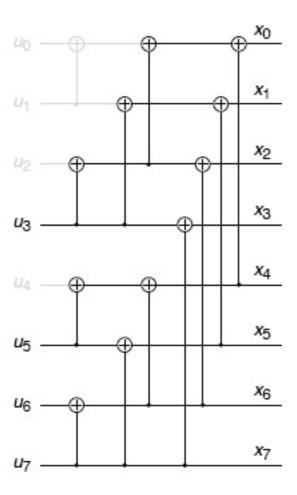


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How to choose the rows?

### Reed-Muller Codes

length  $N = 2^m$ ,  $m \in \mathbb{N}$ 

generator matrix: rows of  $G_2^{\otimes m}$ 

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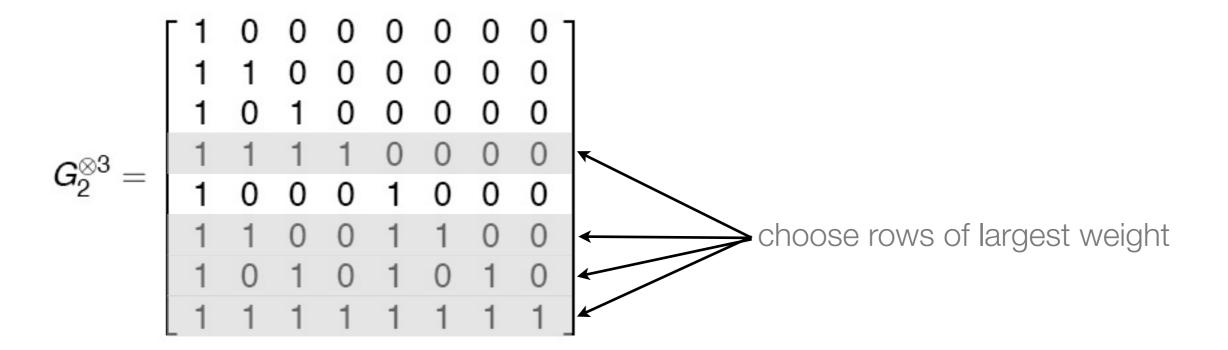
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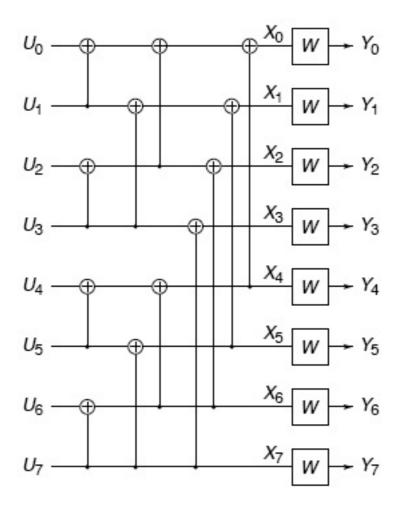
generator matrix: rows of  $G_2^{\otimes m}$ 

How to choose the rows?

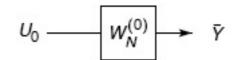


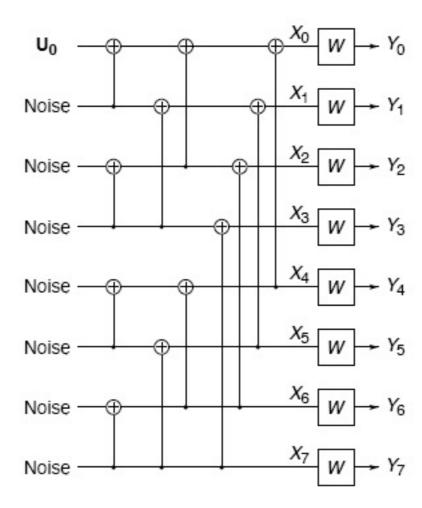
$$\bar{x} = [0\ 0\ 0\ u_3\ 0\ u_5\ u_6\ u_7]G_2^{\otimes 3}$$

## Polar Codes

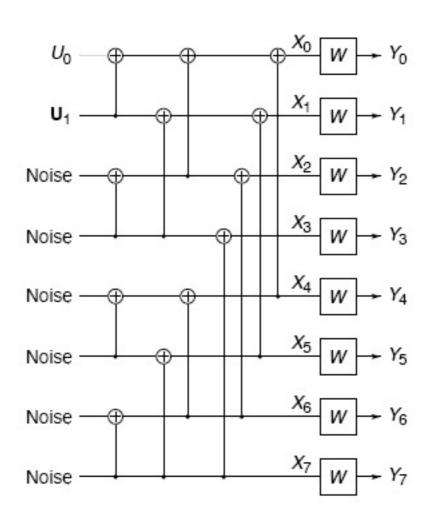


W -- BMS channel

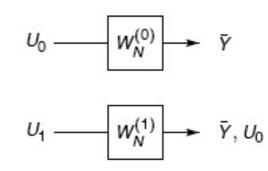


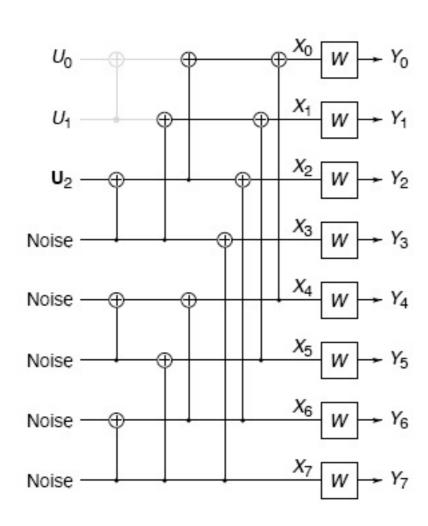


W -- BMS channel

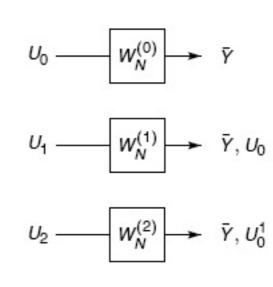


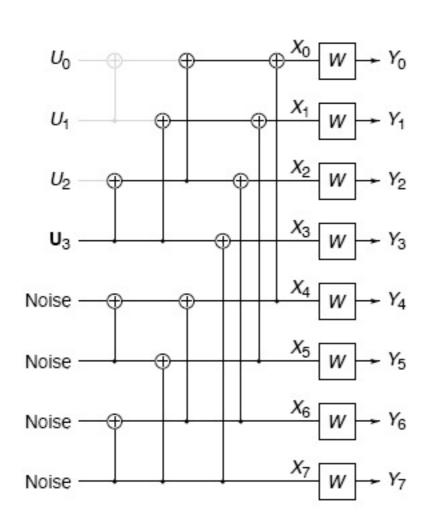
W -- BMS channel



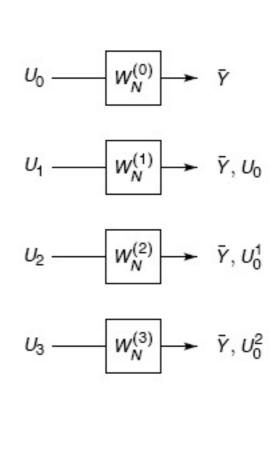


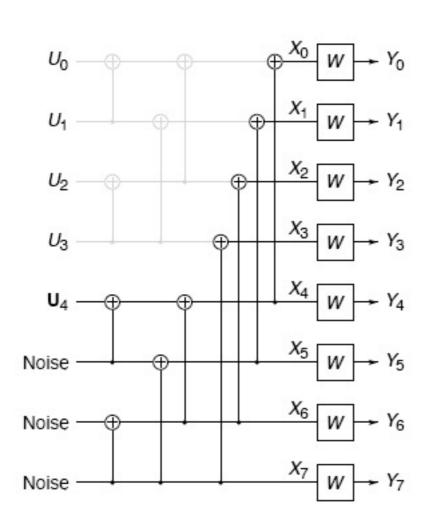
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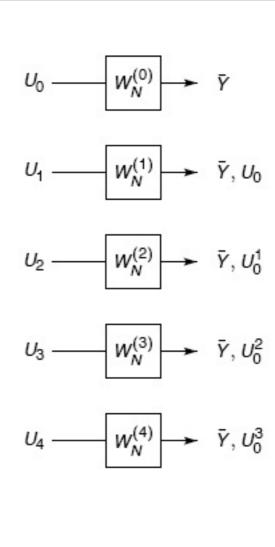


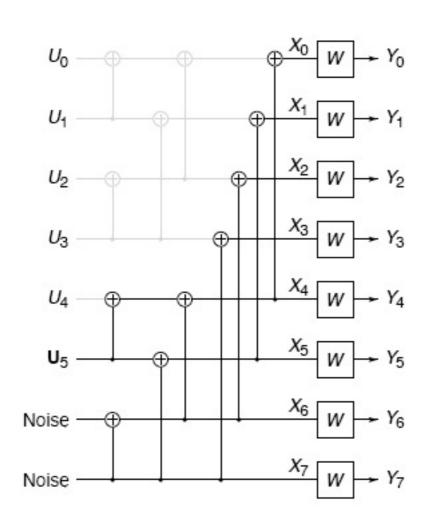
W -- BMS channel



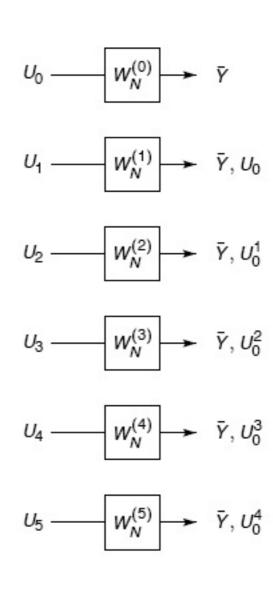


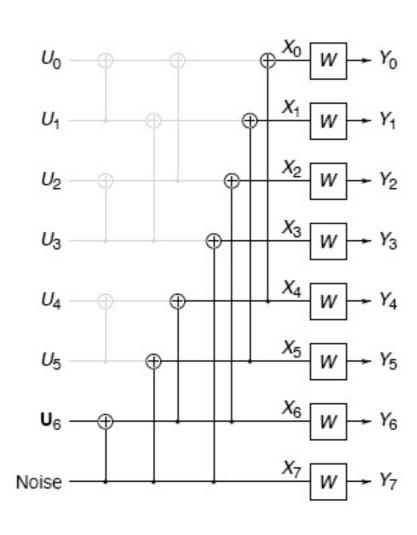
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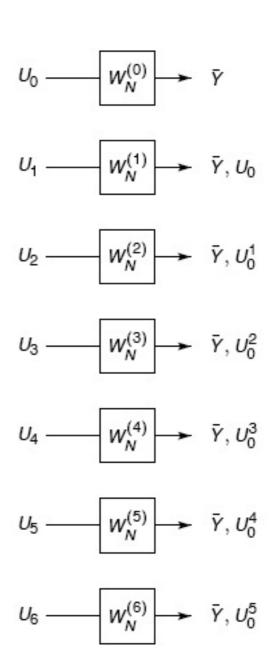


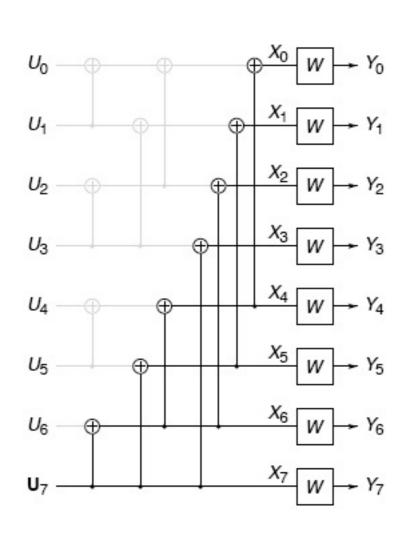
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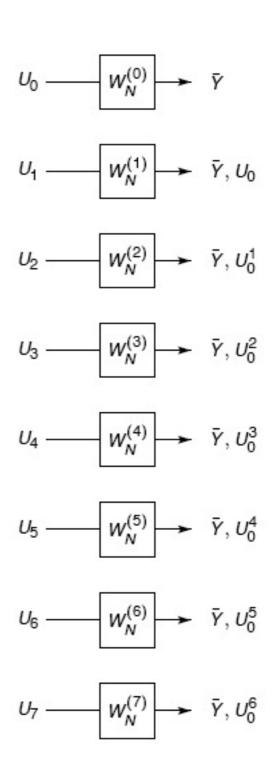


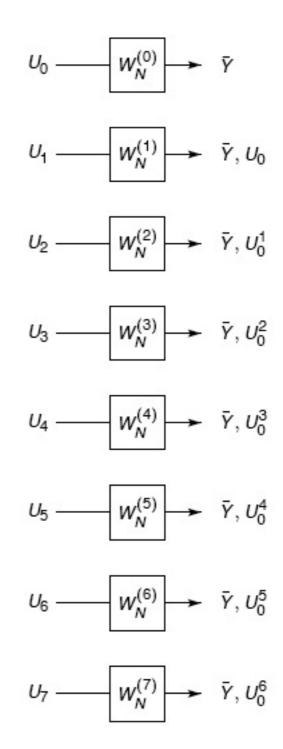
W -- BMS channel



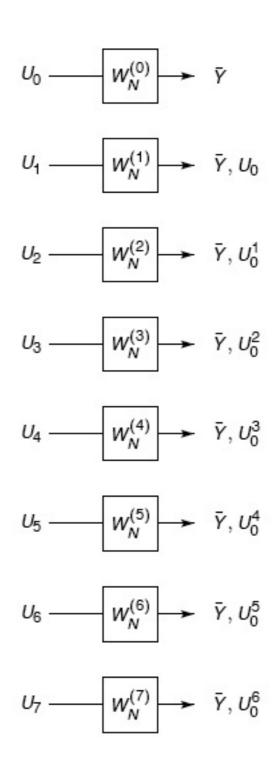


W -- BMS channel



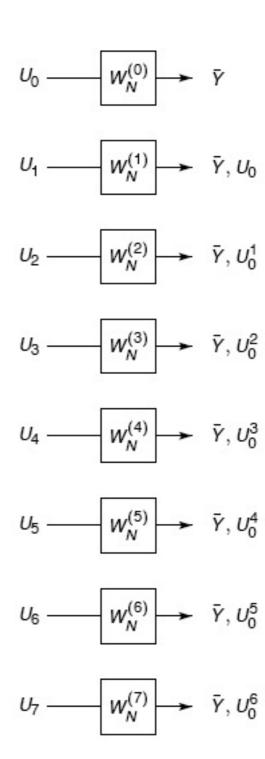


as  $N \to \infty$ , channels polarize, either completely noisy or noise-free



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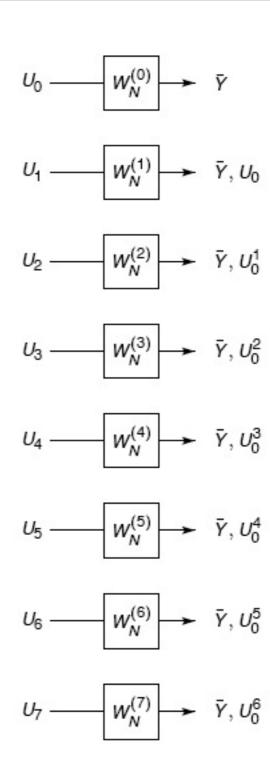
fraction of good channels approaches capacity I(W)

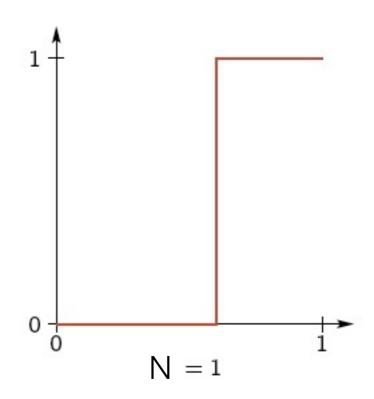


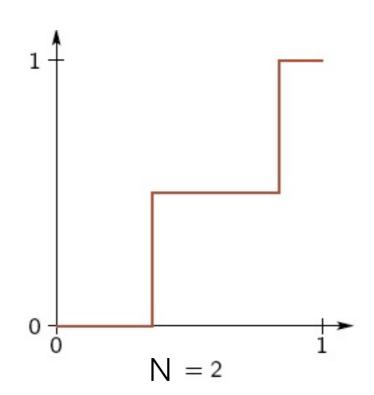
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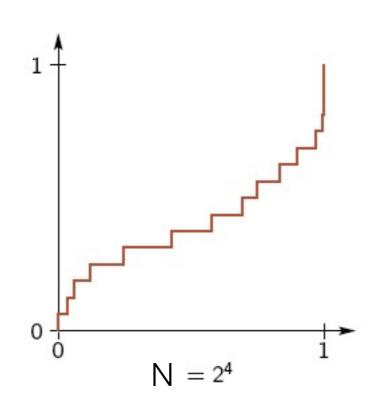
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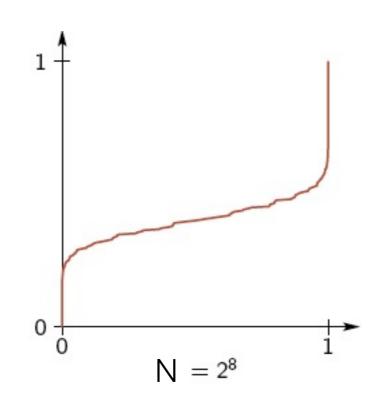
fix bad channels and transmit uncoded bits over the good ones

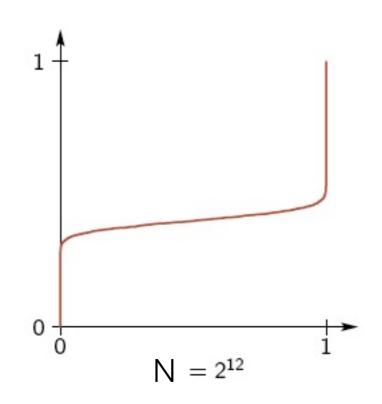


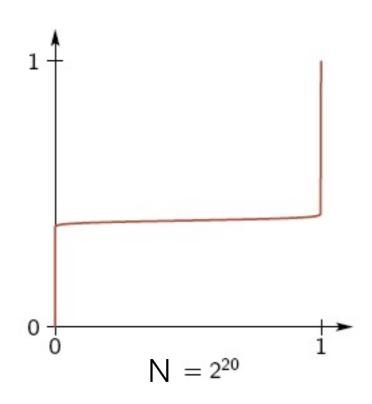


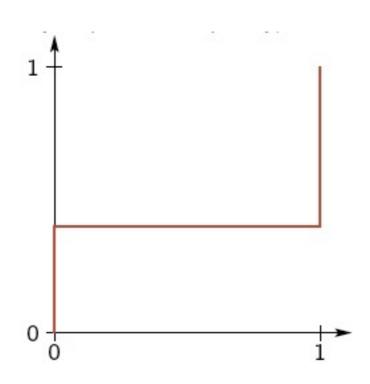


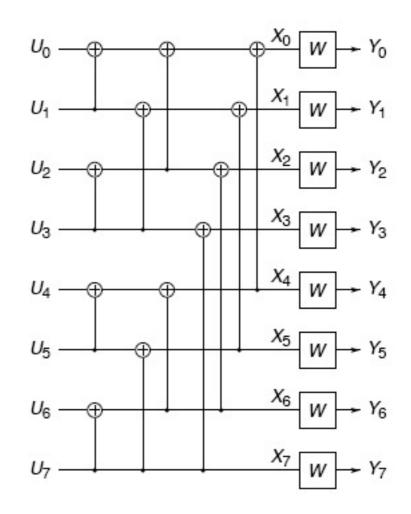




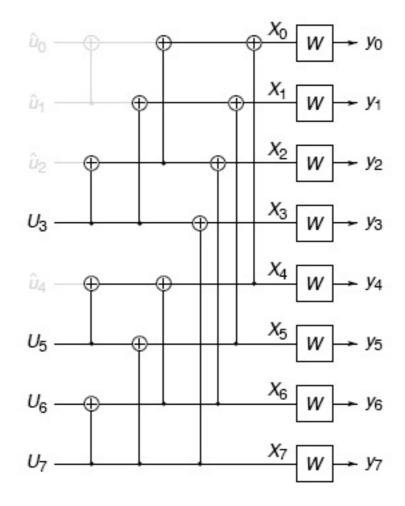




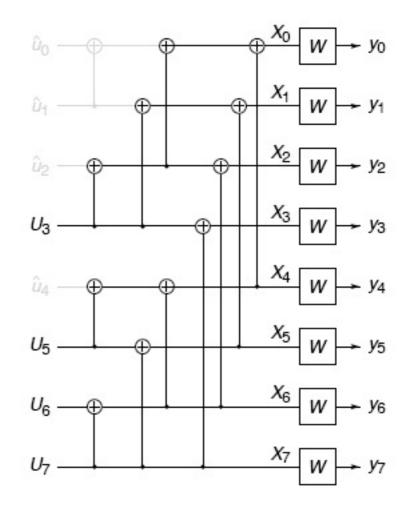




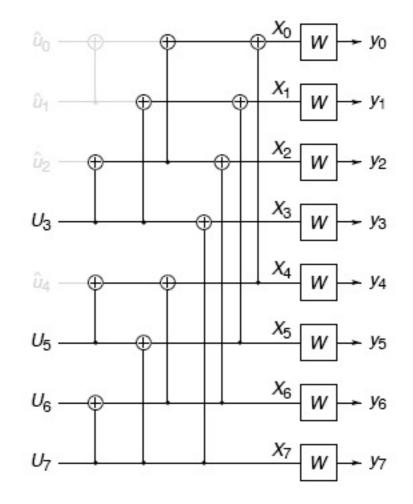
$$F = \{0, 1, 2, 4\}$$



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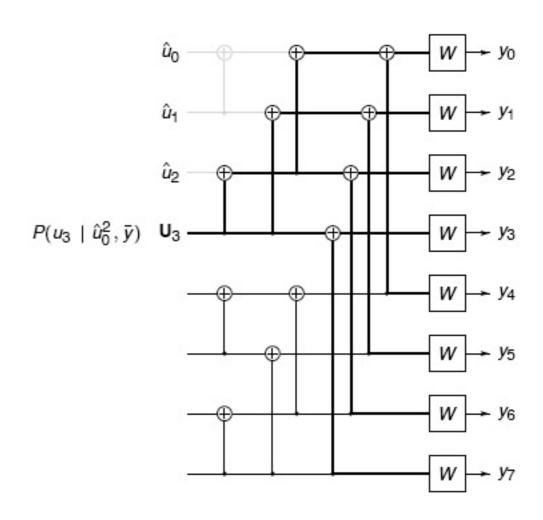
$$F = \{0, 1, 2, 4\}$$
From 0 till  $N - 1$ 
if  $i \in F$ ,  $\hat{u}_i = 0$ 
if  $i \in F^c$ ,
$$\hat{u}_i = \left\{ \begin{array}{l} 0, & \text{if } \frac{P(0|\hat{u}_0^{i-1}, \bar{y})}{P(1|\hat{u}_0^{i-1}, \bar{y})} > 1 \\ 1, & \text{otherwise} \end{array} \right.$$



$$F = \{0, 1, 2, 4\}$$

if 
$$i \in F$$
,  $\hat{u}_i = 0$  if  $i \in F^c$ ,

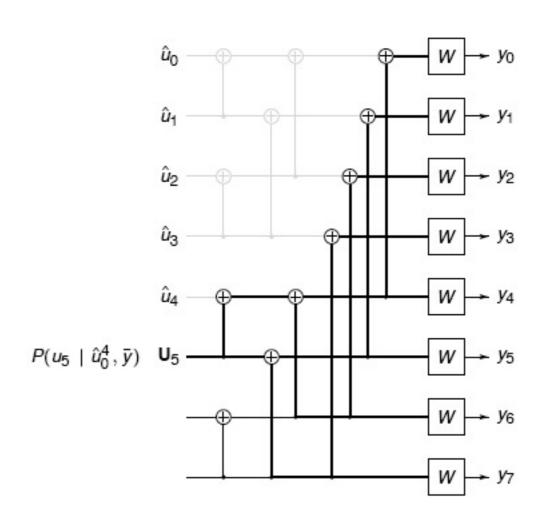
$$\hat{u}_i = \begin{cases} 0, & \text{if } \frac{P(0|\hat{u}_0^{i-1}, \bar{y})}{P(1|\hat{u}_0^{i-1}, \bar{y})} > 1\\ 1, & \text{otherwise} \end{cases}$$



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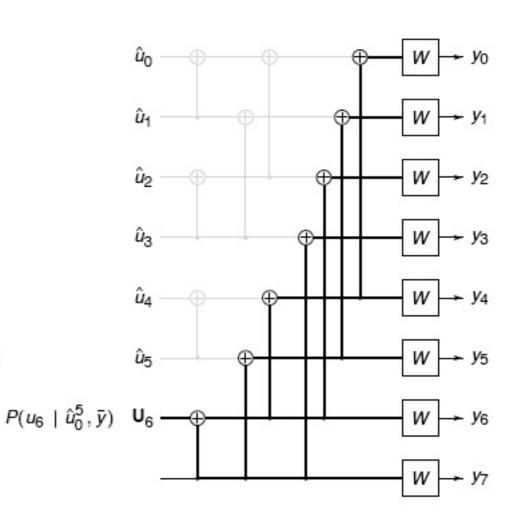
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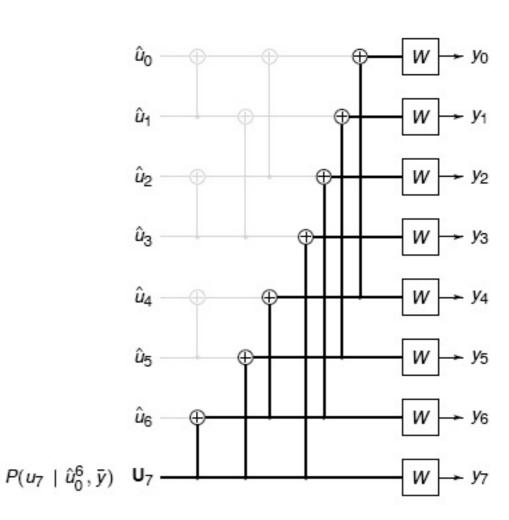
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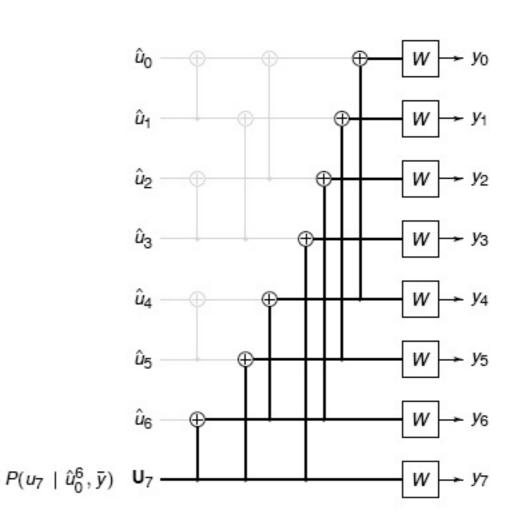
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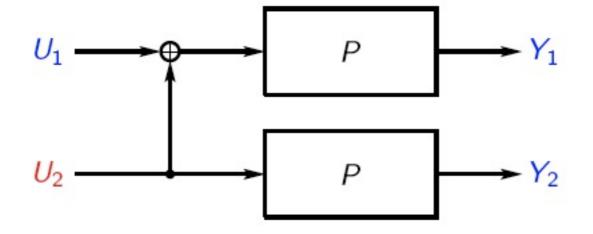
From 0 till N-1

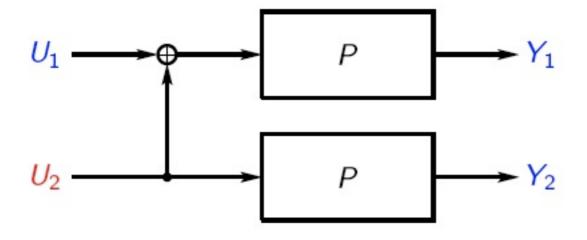
$$\begin{array}{l} \text{if } i \in F, \ \hat{u}_i = 0 \\ \text{if } i \in F^c, \end{array}$$

$$\hat{u}_i = \begin{cases} 0, & \text{if } \frac{P(0|\hat{u}_0^{i-1}, \bar{y})}{P(1|\hat{u}_0^{i-1}, \bar{y})} > 1\\ 1, & \text{otherwise} \end{cases}$$

Complexity  $O(N \log N)$ 

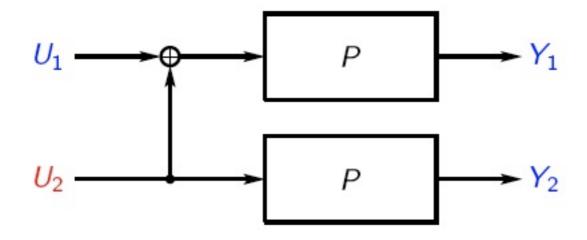






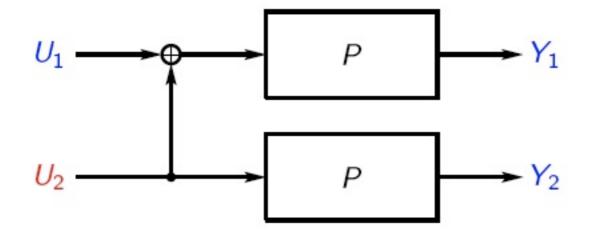
$$P^{-}(y_1y_2|u_1) = \sum_{u_2} \frac{1}{2} P(y_1|u_1 + u_2) P(y_2|u_2)$$

$$P^+(y_1y_2u_1|u_2) = \frac{1}{2}P(y_1|u_1+u_2)P(y_2|u_2)$$

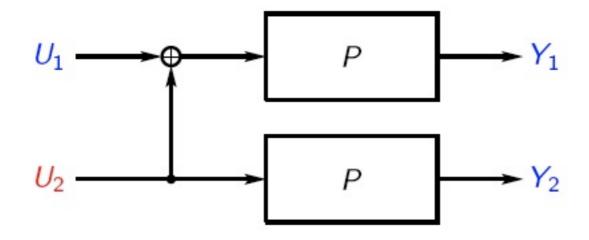


$$I(P^{-}) = I(U_1; Y_1 Y_2)$$

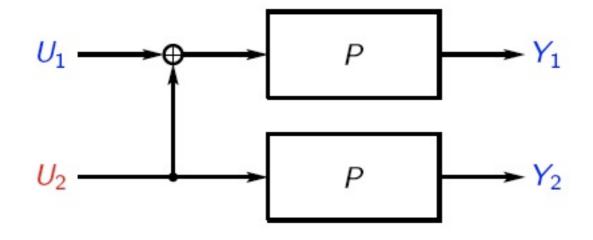
$$I(P^+) = I(U_2; Y_1 Y_2 U_1)$$



$$I(P^{-}) + I(P^{+}) = I(U_1U_2; Y_1Y_2)$$
  
=  $I(X_1; Y_1) + I(X_2; Y_2)$   
=  $2I(P)$ ,

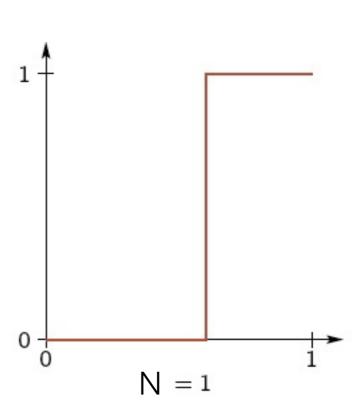


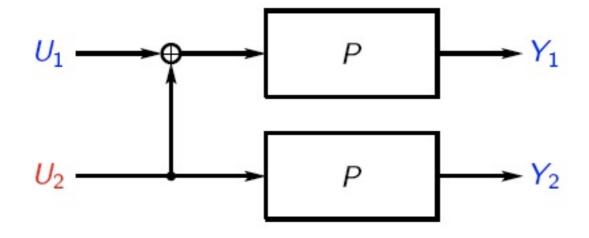
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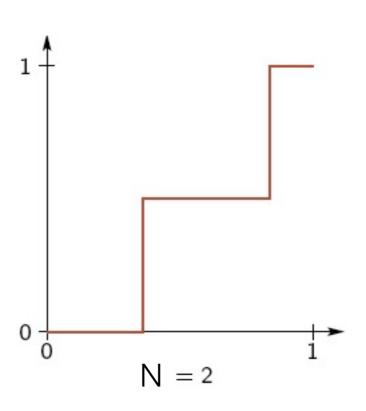
$$I(P^-) \leq I(P) \leq I(P^+)$$

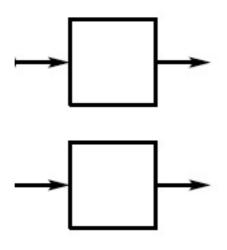


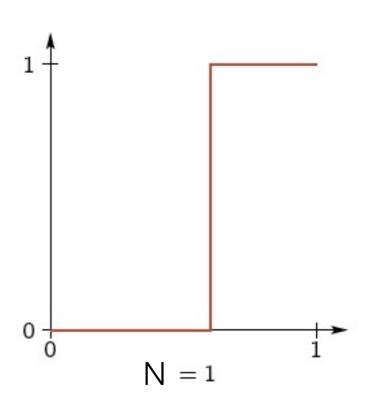


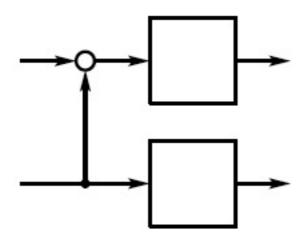
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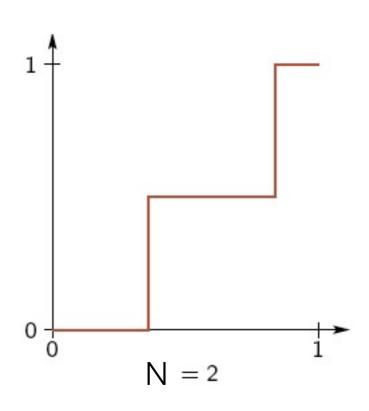
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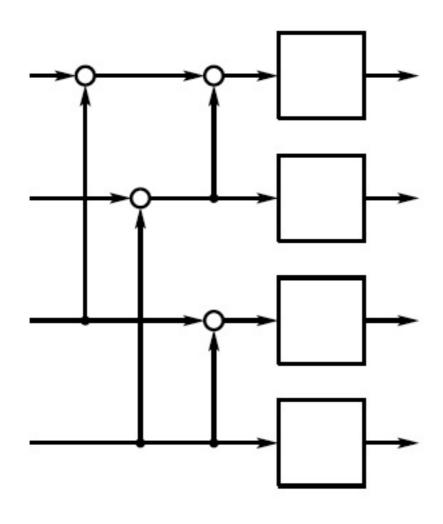


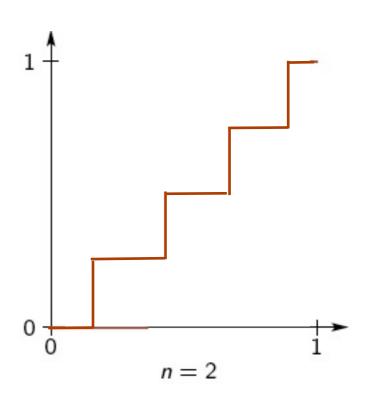


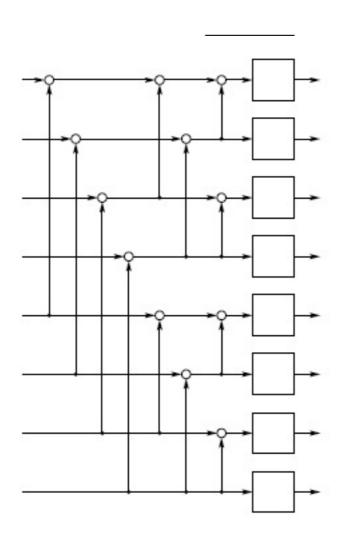


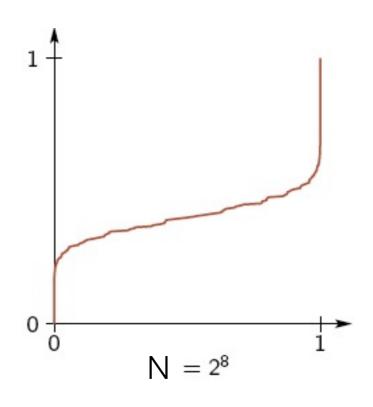












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Study the distribution of In

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Conditional on  $B_1$ ,  $B_2$ , ...,  $B_n$ , and with  $P = W^{B_1, B_2, ..., B_n}$ ,  $I_{n+1}$  can only take on the two values  $I(P^+)$  and  $I(P^-)$ 

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Further,  $E[I_{n+1} \mid B_1, B_2, ..., B_n] = (I(P^+) + I(P^-))/2 = I(P)$ , so  $\{I_n\}$  is a (bounded) martingale

a bounded martingale converges almost surely

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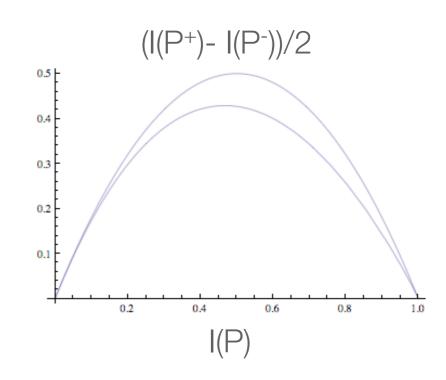
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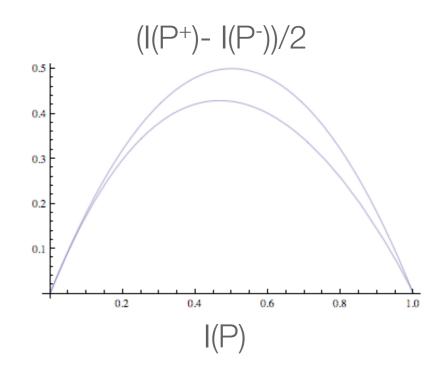
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we conclude that  $I_{\infty}$  takes values only in  $\{0, 1\}$ 



achieve capacity on memoryless channels Arikan 2007

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$$P_B(N) \approx 2^{-N^{\frac{1}{2}}}$$

Arikan and Telatar 2008

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Korada, Sasoglu, and U. 2009

#### Polar Codes Based on Larger Matrices

In [Arıkan08] generator matrix is constructed from the rows of  $G_2^{\otimes m}$ , where

$$G_2 = \left[ \begin{array}{cc} 1 & 0 \\ 1 & 1 \end{array} \right]$$

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Consider codes constructed from  $G^{\otimes m}$ , where G is an  $\ell \times \ell$  matrix. Blocklength  $N = \ell^m$ ,  $\bar{x} = \bar{u}G^{\otimes m}$ 

#### Characterization of Exponent

#### Theorem (Korada,Şaşoğlu,Urbanke)

For any R < I(W), and  $\ell \times \ell$  matrix G,

$$P_B(N) \approx 2^{-(N)^{\mathbb{E}_c(G)}},$$

where 
$$\mathbb{E}_c(G) = \frac{1}{\ell} \sum_{i=1}^{\ell} \log_{\ell} d_i$$
.

$$G = \left[egin{array}{c} g_1 \ dots \ g_i \ g_{i+1} \ dots \ g_\ell \end{array}
ight] \qquad d_i = exttt{dmin}(g_i, \langle g_{i+1}, \dots, g_\ell 
angle)$$

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$$d_1 = 1$$
,

$$G = \left[ \begin{array}{ccc} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{array} \right]$$

$$d_1 = 1, d_2 = 2,$$

$$G = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix}$$

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$$E_c(G) = \frac{1}{3}(\log_3 1 + \log_3 2 + \log_3 2) = 0.42062$$

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/ (III(ai) 2001

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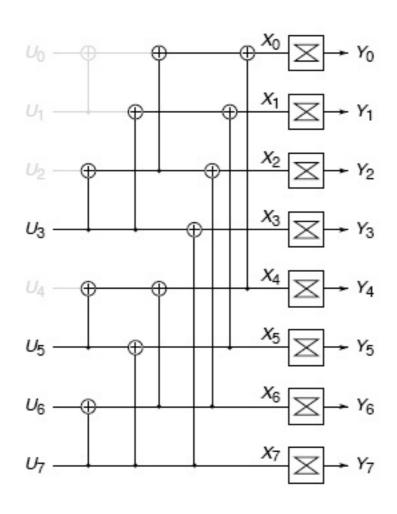
optimal for lossy source coding, Wyner-Ziv, Gelfand-Pinsker, ...

Arikan and Telatar 2008

Korada, Sasoglu, and U. 2009

Korada and U. 2009

#### Source Coding



Y-binary symmetric source d(0,1)=1, d(0,0)=d(1,1)=0  $\bar{Y}$ - source word,  $\bar{X}$ -reconstruction wor  $\frac{1}{N}\mathbb{E}[d(\bar{X},\bar{Y})] \leq D$   $R>1-h_2(D)$ 

# Source Coding

trellis based quantization [Viterbi and Omura], constraint length to infinity

LDGM based quantization [Martinian and Yedidia], [Wainwright and Maneva], [Ciliberti and Mézard], [Filler and Fridrich], works well in practice

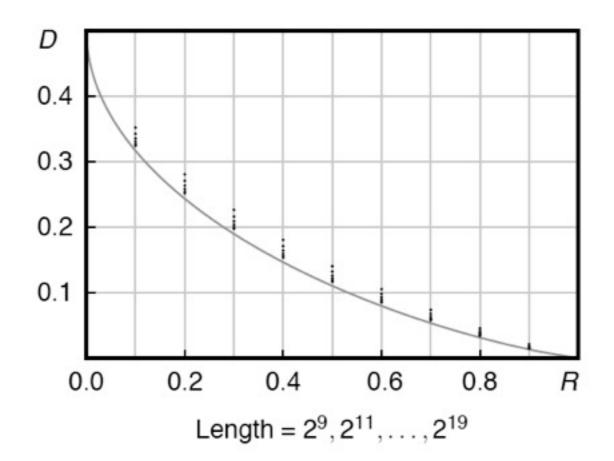
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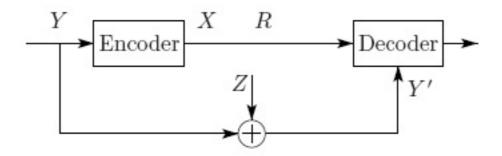
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scaling

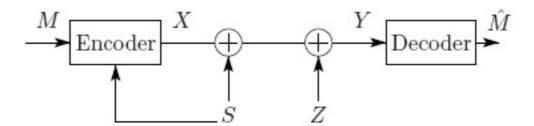
# Summary

- + completely new paradigm of coding
- + provably achieves capacity
- + low complexity
- + many applications
- currently only competitive for VERY large N

#### Wyner-Ziv and Gelfand-Pinsker



**Figure 4.1:** The Wyner-Ziv problem. The task of the decoder is to reconstruct the source Y to within a distortion D given (Y', X).



**Figure 4.4:** The Gelfand-Pinsker problem. The state S is known to the encoder a-causally but not known to the decoder. The transmission at the encoder is constrained to have only a fraction D of ones on average, i.e.,  $\mathbb{E}[X] \leq D$ .